Sensitivity and calibration of non-destructive evaluation method that uses neural-net processing of characteristic fringe patterns

Arthur J. Decker, Kenneth E. Weiland
NASA Glenn Research Center, 21000 Brookpark Rd., Cleveland, OH 44135-3191

ABSTRACT

This paper answers some performance and calibration questions about a non-destructive-evaluation (NDE) procedure that uses artificial neural networks to detect structural damage or other changes from sub-sampled characteristic patterns. The method shows increasing sensitivity as the number of sub-samples increases from 108 to 6912. The sensitivity of this robust NDE method is not affected by noisy excitations of the first vibration mode. A calibration procedure is proposed and demonstrated where the output of a trained net can be correlated with the outputs of the point sensors used for vibration testing. The calibration procedure is based on controlled changes of fastener torques. A heterodyne interferometer is used as a displacement sensor for a demonstration of the challenges to be handled in using standard point sensors for calibration.

1. INTRODUCTION

NASA Glenn has been using neural nets to detect structural changes and damage.[1] A neural net can be trained to detect very small changes in the characteristic patterns of the modes of a vibrating structure. The characteristic patterns are recorded using electronic or television holography. Modeling has shown that the sensitivity should be 10 nanometers or less.[2] Here sensitivity refers to the maximum shape change (as opposed to a simple amplitude change) in the vibration-displacement distribution. The displacement changes can be induced by damage such as cracking, by changes in fastener torques, or by variations in the mode mix of the vibrating structure. An important feature for damage detection is that the sensitivity can be controlled. In particular, the neural-net can be trained to be insensitive to irrelevant changes.

NASA has supported this work to promote safety in the operation of ground test facilities or aviation safety, in general. There is value in being able to detect the gradual on-set of structural changes or structural damage in a turbo-machine component or other structural component. Such changes possibly can occur when the component is operated outside its design envelope, where said operation might occur frequently in a ground-test facility. Or changes might occur for unforeseen reasons in a component being tested or operated normally. Hence, the development of non-intrusive optical inspection systems such as neural-net-processed electronic holography is justified.

The step-by-step non-destructive evaluation (NDE) procedure has been reported elsewhere.[1,3-5] These reports have explained a data folding technique for maximizing the sensitivity of the neural nets for damage detection. The practical application of the NDE procedure has required answering some additional questions which are addressed in this paper.

In particular, determining the sensitivity of the NDE method as a function of sample size is important. The full image of a characteristic pattern contains 640x486 pixels, but the current computer-based neural nets handle no more than about 10,000 pixels. A typical sample size is 2000 pixels. Hence, the characteristic pattern must be sub-sampled before neural-net processing. The training-set size increases as the square of the number of samples per pattern; hence minimizing the number of samples per pattern is desirable. Furthermore the structure can be sub-divided into multiple regions of fixed sample size, where the training-set size increases only linearly with the number of regions. One consequence is that inspecting multiple regions of minimum size may be the most efficient process. This paper shows how sensitivity varies with the sample size for simple structures.

Another objective is that the NDE method be calibrated or quantified in a manner acceptable to the NDE community. The NDE method requires excitation of vibration modes at low amplitudes; hence the objective was to make the calibration or quantification process conform to NASA's vibration-test handbook.[6] A mutually acceptable approach was to vary the vibration-mode shapes and, therefore, the characteristic-pattern shapes by changing fastener torques. Space craft or other structures either have fasteners or are mounted in fixtures with fasteners for testing. Torques can be varied in a repeatable and measurable manner, and the consequent change in the mode shapes can be detected. Modes typically are excited using a siren or a piezoelectric vibrator. The optical inspection technique can, in principle, be compared with measurements made with conventional accelerometers, strain gauges or displacement gauges. This paper discusses the variation of neural-net output as a function of fastener torque for simple structures.

A final objective of this paper is to discuss the practical sensitivity of the neural-net inspections. The laser speckle effect was the only noise source for the model-generated estimate of sensitivity of 10 nanometers. But a test object is actually subjected to random excitations of vibration modes in addition to the mode being excited for inspection. There are also fluctuations in the laser illumination of the test object including pointing instabilities and perhaps mode hops. Hence, the vibration-mode mix, the vibration-displacement distribution, and the hologram interference phase may vary at random. The first vibration mode of an object can be especially troublesome, generating excitations in the 10 nm to 200 nm range, even on a vibration isolation table. Fortunately, the neural net can be trained to be insensitive to excitations of the first mode. The spurious vibration fluctuations depend on the geometry and material of the structure. A consequence of the noise sources as well as the net training error is that the output of the neural net will fluctuate, and statistical analysis may be necessary to estimate the significance of indications of structural changes.

This paper begins with a brief review of the neural-net NDE method. The method is discussed extensively in the references.[3-5] This paper discusses only its application to a calibration test plate that was originally intended to mount fiber-optic strain gauges.[7] The plate is held in vise-grip mounts with fasteners that can be adjusted. The specific electronic-holography setup and implementation used for this work are also described briefly. Measurements, showing the performance of the neural-net inspection method as a function of sample size, are presented for copper and aluminum plates. The variation of the neural-net output as a function of torque is shown for different vibration modes of the plates. The performance of the neural-net for damaged detection is compared with that of a heterodyne interferometer. The effect of first-mode noise is presented. Analysis of Variance (ANOVA) methods are used to test the significance of the results..

2. NDE METHOD , TEST SETUP AND TEST ENVIRONMENT

Figure 1 shows a setup[5] used to test the calibration and quantification of the neural-net inspection method. The object in Fig. 1 is a simple plate made either from copper or aluminum. The plates were held between two aluminum vise-grip mounts. Each mount was closed with four screws. The torque of the second screw from the top on the left was adjusted to vary the mode shapes. The torques of the other screws were adjusted to, and kept fixed at, 70 in lb. The television-holography (electronic-holography) camera, seen in the figure, is zoomed to observe only the portion of the plate between the grips. The vice grips are not recorded for the tests. Hence the effects of fastener-torque variations will be detected only in the changes of the characteristic patterns of the visible portions of the plates. In effect, the vibration modes are being exploited as remote gauges and health monitoring devices. The visible part of the copper plate was then 138.07 mm wide by 102.68 mm high. The thickness of the copper plate was 0.85 mm. The visible portion of the aluminum plate was 138.07 mm wide by 102.55 mm high. The thickness of the aluminum plate was 1.24 mm. The stiffer aluminum plate has a smaller noise-excited first mode than the copper plate, but of course laser-beam fluctuations are unaffected. The vibration modes were excited with a siren. A heterodyne interferometer was used to monitor the excitation level. The interferometer was also used to monitor the vibration-noise level on the vibration-isolation table where the tests were performed.

The characteristic patterns were generated in the simplest manner possible. In the method, 2 holograms of the vibrating structure are recorded in adjacent frames in 2 fields at 30 frames per second. The reference-

beam is phase-shifted by π between frames, and the holograms are subtracted. The absolute value of the pattern is displayed for visualization purposes. Patterns can be averaged and image-processed to improve visualization. Other forms of electronic holography could have been used as well for visualization or quantitative analysis, requiring four or more holograms for each characteristic pattern. The neural-net NDE method was intended for real-time processing and employs only two holograms per characteristic pattern to maximize speed. Figure 2 displays characteristic patterns of the copper plate. The patterns in Fig. 2 were assembled from more than two holograms per pattern to improve visualization and to average speckle-effect and electrical noise.
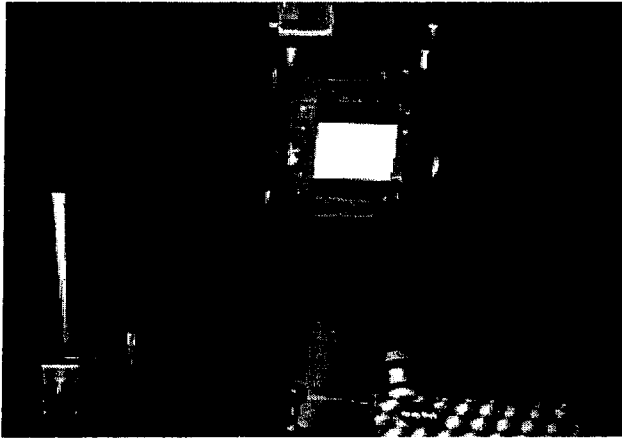

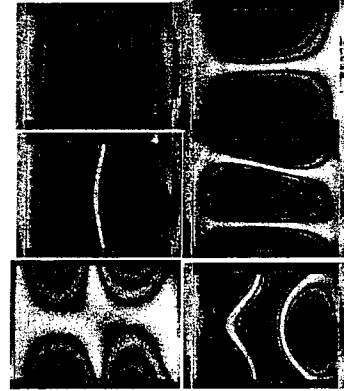Fig. 1: Electronic holography setup for testing and calibrating NDE method.

Fig. 2: Characteristic patterns of copper test plate in Fig. 1. Frequencies of modes increase left to right and top to bottom.

The NDE method actually processes only a sub-sampled version of the TV-resolution characteristic patterns. Adjacent holograms are sub sampled typically at about 2000 locations chosen at random within prefigured tiles called large pixels. Note that there is no averaging within a large pixel and that the entire pixel is defined by a sub sample. Sub-sampled adjacent holograms are then subtracted to produce a sub-sampled characteristic pattern. Figure 3 shows a sub-sampled pattern for the fourth mode of the aluminum plate containing 6912 samples. One advantage of random sub sampling is that it is easy to assemble a set of uncorrelated speckle patterns for the same characteristic pattern. A feed-forward neural network learns to ignore the details of the speckle patterns, if it is trained with enough uncorrelated speckle patterns of the same mode. In general, that number has been know for some time to be 10 percent of the number of samples per pattern.[8] Hence, 200 uncorrelated speckle patterns per mode would be required for a sample size of 2000 pixels. The storage requirement of the training set is proportional to both the sample size and the number of training records; hence the training-set storage requirement increases as the square of the sample size.
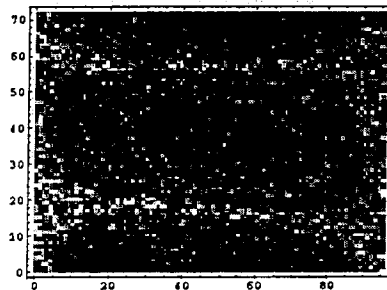

Fig. 3: Sub-sampled version of fourth mode of aluminum plate
(similar to fourth mode of copper plate in fig. 2) containing 96x72 samples.

Another reference[4] presents in detail a general viewpoint of the categorization and assembly of training sets for NDE. Simply put, for the examples discussed herein, only two categories of training records were created. A training record consists of a sub-sampled characteristic pattern and an output index to be encoded with two or three output nodes. One category of training records consisted of a single vibration mode of the unchanged or undamaged structure. The trained net then monitored that mode for any changes or damage. A training value was selected for the output index of the mode. Typically, the pair [0.8, 0.2] was used as the training output for the feed-forward neural networks used for the tests. Two nodes or neurons are used to encode the index. The feed-forward net typically employs the sigmoid transfer function for the hidden and output nodes, and that requires the choice of fractional indices. The second training category consisted of several modes, typically three. One of these second-category modes consisted of the zero-amplitude condition. The zero-amplitude condition typically is corrupted with an environmentally-excited low-amplitude excitation of the first mode as well as the effects of laser-beam fluctuations. Random excitations of the first mode with amplitudes between 10 and 200 nanometers appeared in preparing the training sets for this paper. All of the modes in the second training category were assigned the same index where the pair [0.2, 0.8] was used for a feed-forward neural net.

A neural network was trained using the two categories of training records. The typical feed-forward net has one hidden layer. About three hidden-layer nodes are required per category; hence the two-category case requires six hidden-layer nodes. The training time depended on the size of the training set. A net to be discussed below was trained on characteristic patterns containing 6912 samples. The training time on a SGI O2 workstation was about 20 minutes. Training on 1728-sample patterns was much faster and required only 3.5 minutes.

The key result of training on two categories was that the output of the net becomes sensitive to changes in the shape of the net-monitored characteristic pattern. The large value of the index pair is called the Degradable Classification Index (DCI). The DCI varies from about 0.8 for the original training pattern of the mode being monitored to 0.2 as that characteristic pattern changes substantially. A change in the shape of the characteristic pattern implies a change in the shape of the vibration-displacement distribution, if other phase fluctuations of the laser illumination can be ignored. The vibration-displacement distribution changes because of damage, because of variations in fastener torques, or because of changes in the mix of vibration modes. The mix of vibration modes varies during a test because of random variations in the amount of environmentally excited first mode. The net can be trained to ignore the effect of the first mode.

The current estimate of sensitivity is based on models and computer experiments. The net's observed sensitivity to changes in the characteristic pattern has proven to depend on the training mode mix and the number of sub-samples. Those quantities were originally set by trial and error for each application.[1] The current work, still in progress, is directed to quantifying, calibrating and controlling the sensitivity of the net inspection method. The results to be presented below were generated by the method and setup that was summarized briefly in this section of the paper. Both the method and the setup are controlled by a locally-written software package and are described in more detail in the references. The approach for evaluating the measured results is discussed next.

3. APPROACH

The approach is to graph the data uniformly for discussion purposes, but caution must be exercised, since the statistical properties often are not constant even for a single run of torque settings. One advantage of the NDE method is that it works well qualitatively in the presence of fluctuations that make statistical or quantitative analysis as well as point-sensor measurements difficult.

The results consist of the DCI values as a function of screw torque, number of sub samples per characteristic pattern and plate material. The excitation level and the vibration noise level were monitored at the same point on the plate during the tests to assure repeatability. Monitoring was done with a heterodyne interferometer. The same conditions can then be repeated for tests of other NDE methods to be used for calibration or

quantification. The interferometer was also used as an example of a point-measurement device for detecting the effect of the screw torque on the vibration-mode shape.

Analysis of variance (ANOVA) methods were used to test the significance of the DCI for different screw torques and varying numbers of sub samples. The results are based on 100 characteristic patterns per setting. The variances often are not uniform, and the data may deviate from strictly normal because of outliers. Figure 4 shows a box plot for an extreme case. The first and second training categories, for this case, actually consisted of a single mode (and the zero-amplitude condition), but the mode was recorded at two different torque conditions of 0 and 70 in lb for the second category. The first training category was recorded at 25 in lb. The DCI then varies over the entire output range of the net from 0.8 to 0.2, but the variances clearly differ substantially.
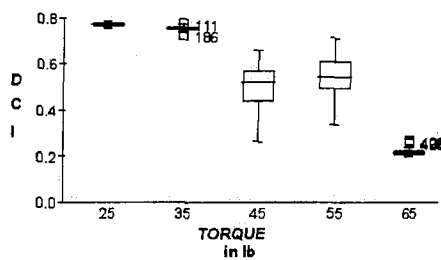

Fig. 4: Extreme example of non-constancy of variance. Variations of same mode used for training to exploit the full output range of the net. Integers label outliers.
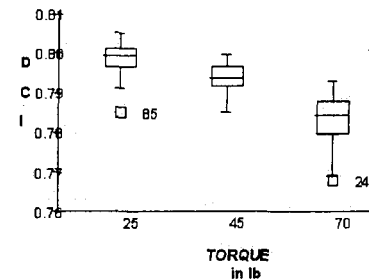
Fig. 5: Example of raw results where variances do not change significantly, but where full range of net is not exploited. Integers label outliers.

ANOVA could be performed with unweighted comparisons of means or medians, or with weighted comparisons of means or medians. Figure 5 shows a box plot of data suitable for an unweighted comparison of means. Figure 4 by contrast was deemed suitable for a weighted comparison of means. A commercial software package was used for these decisions and comparisons.[9]

The choices in this paper were to treat all the data in a plot as statistically uniform (homoscedastic) and to plot an unweighted simultaneous comparison of means. This approach, although not strictly correct, is actually somewhat conservative. The objective is to show how the DCI is a sensitive indicator of a varying mode shape in the presence of noise sources and how it decreases in general as the mode shape changes from a training value. That decrease can then be correlated with other measurements for quantification or calibration purposes. The weighted comparisons and the comparisons based on medians by contrast indicated significant differences more readily than the unweighted comparison of means used for the plots. In any case, there were no differences in the overall conclusions when applying all the forms of ANOVA to the same data. Linear regression was performed for some of the data and proved as expected to be a more sensitive predictor of variation than ANOVA. But ANOVA suffices for the discussions of this paper.

The next section presents and discusses the sensitivity of the NDE method as a function of sample size.

4. SENSITIVITY AND SAMPLE SIZE

The copper plate was used to evaluate the sensitivity of the neural-net inspection method as a function of sample size. Tests were performed for 4 sampling arrays of 12x9=108, 24x18=432, 48x36=1728, and 96x72=6912 samples. The excitation levels of the modes and the vibration noise were monitored with the heterodyne interferometer at a point 69.6 mm from the top edge of the plate and 43.6 mm from the left vise grip. This location is not quite at the maximum excitation point of the first mode (the center), but is close. The

The second training category consisted of the zero-excited condition, the 2nd mode at a peak-to-peak interferometer reading of 430 nm and the 3^{d} mode at 540 nm. Resonant frequencies were about 201 Hz, 364 Hz and 472 Hz for the 2nd, 3^{d} and 5th modes, respectively. The zero-excitation condition of course contained the random effects mentioned earlier. Spurious vibrations tend to vary, but levels as high as 200 nm peak-to-peak were observed for the copper plate at especially noisy times. The range 50 nm to 100 nm was more typical. These measurements of course were executed close to the node line of the 5th mode and do not represent the peak vibration amplitude of the 5th mode. But the measurements are close to the peak vibration point of the noise-contributing 1st mode.

The neural-nets were trained to an root-mean-square error of less than 0.01. The computer resources required for training varied with the sample size. The raw size of the training file varied from 46 kilobytes for the 108-sample case to 102 megabytes for the 6912-sample case. Training time ranged from 22 seconds for the 108-sample case to 1098 seconds for the 6912-sample case. The net source-code-size ranged from 59 kilobytes for the 108-sample case to 3.5 megabytes for the 6912-sample case. The use of the neural-net technology has proven not to be particularly challenging, if the rules listed in the references are followed. In particular, training time is of little consequence.

Again the data in Fig. 6 are displayed as if the scatter was always normal and the variances were uniform. The plots represent a simultaneous comparison of means. The factors are 25, 45 and 70 in lb. Adequate separation of the DCI levels is not observed for less than 1728 samples. There is an increase in DCI discrimination in going from 1728 samples to 6912 samples.

The 1728-sample condition separates the 3 torque effects. This sample size is conveniently for the hardware-software combination used for the tests. Training time was only about 3.5 minutes, and the training set required only about 11 megabytes. The net source-code was less than a megabyte in size.

The noise level on the vibration-isolation table was high during these tests. It was decided to use a stiffer aluminum plate to reduce the effect of the first vibration mode and separate out other noise effects. The aluminum plate provides another set of results pertaining to the calibration and quantification of the neural-net inspection method. Those results are discussed next.

5. ALUMINUM PLATE

The aluminum plate was inspected in exactly the same way as the copper plate, but the results differed. The 4th mode rather than the 5th mode proved to be the most sensitive to variations in torque. The same aluminum vise grips were used for the aluminum plate as were used for the copper plate. The second training category consisted as before of the zero-excited condition, the 2nd mode and the 3^{d} mode excited at about 0 Hz, 406 Hz and 756 Hz respectively. The 2nd and 3^{d} modes were excited at amplitudes of 520 nm peak-to-peak. The 4th mode was excited at about 915 Hz, but the resonant frequency varied about 6 Hz when the torque of the second fastener was varied from 25 in lb to 70 in lb. The interferometer measured the peak-to-peak amplitude of the 4th mode to be 250 nm. Note again that the measurements are not performed at the maximum-amplitude locations of the modes. The interferometer indicated that the 1st-mode noise levels were only 10 nm to 20 nm peak-to-peak.

Figure 7 shows the DCI of the trained nets for the 1728 and 6912 sub-sample cases. The factor effects are separated in both cases, but only a small fraction of the range of the net is involved. An interesting result was that the scatter of the data decreased by a factor of four when the resolution was increased four times.

The training procedure was modified somewhat in an attempt to increase the DCI range of the net in responding to torques from 25 in lb to 70 in lb. The 4th mode, excited at a zero-torque setting of the adjustable screw, was included in the second training category together with the 2nd mode and the zero-excited mode. The first training category consisted of the 4th mode at a torque of 25 in lb. The DCI range increased, so it was decided to compose the training set entirely of versions of the 4th mode.

Figure 4 as mentioned earlier shows the result of composing the second training category entirely of the 4th mode (and the zero-excited condition), but at different torques. The DCI now covers the entire training range of the net, but the variance changes substantially as a function of torque as was mentioned earlier.

DCI

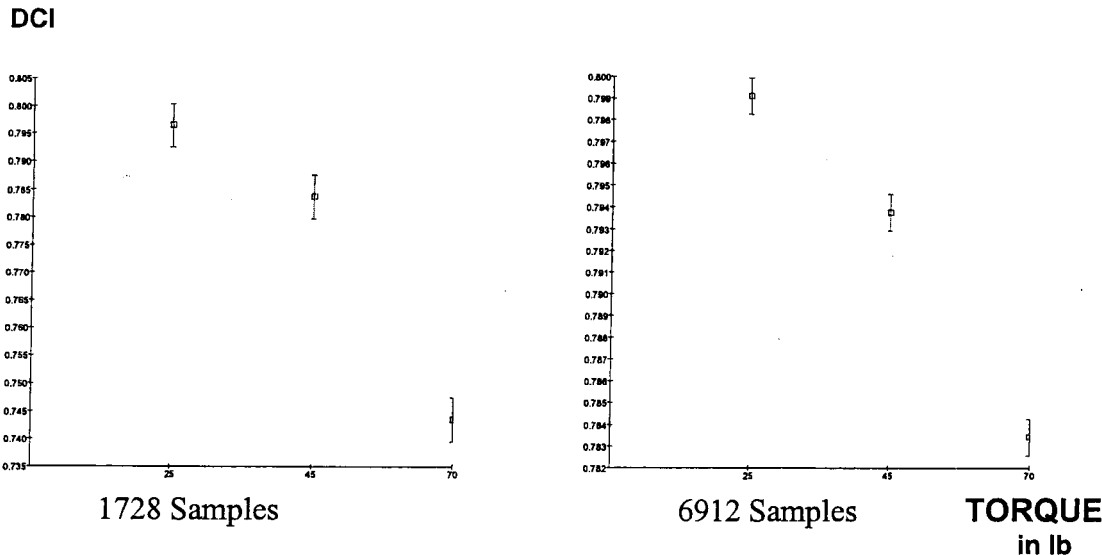| 1728 Samples | 6912 Samples | **TORQUE** |
| | | **in lb** |

Fig. 7: Response of trained net to fourth mode of aluminum plate as a function of screw torque and for two sample sizes.

The next section presents a brief discussion of the approach to calibration and quantification using the heterodyne interferometer as an example of a displacement detector. The next section also shows how first-mode noise has a negligible effect on sensitivity.

6. QUANTIFICATION OF NDE METHOD

The calibration of the neural-net inspection method to be consistent with the NASA vibration-test standards was an on-going effort at the time this paper was written. But the approach and the optical elements of the NDE method are now complete. As stated the approach is to co-vary the responses of the net and other sensors by varying fastener torques. The approach was demonstrated by using the heterodyne interferometer as a point-measurement sensor. Also, the response of the net was measured for varying amounts of contamination by the 1st mode. The stiffer aluminum plate was used for this test to allow the response to the 1st mode to be measured at smaller amplitudes. The net learns by example to ignore substantial amounts of 1st-mode noise.

Figure 8 shows the response of the heterodyne interferometer to variations in fastener torque. The data were collected for the copper plate and represent the same torque conditions used to generate Fig. 7. Each torque value shows the results of twenty measurements. A measurement consisted of the difference in amplitude between the interferometer reading at the monitoring point and the interferometer reading at a point 50 mm to the right. The interferometer was moved back and forth repeatedly on a motor-driven translation stage until all the measurements were acquired for each torque setting. The data were acquired for the 2nd mode. The 2nd mode showed the second largest variation in resonant frequency as a function of torque and a larger variation in interferometer output than the 5th mode. The excitation level was about 1000 nm peak-to-peak, but 1st-mode variations as large as 100 nm were observed. The heterodyne interferometer was not able to distinguish the different torque settings unlike the neural net.

The NDE method, based on characteristic patterns and neural nets, is quite robust. In particular, the net learns by example to ignore the 1st mode. Figure 9 shows that the net output and sensitivity are not much

affected by 1st mode levels as high as 90 nm peak-to-peak. These measurements were acquired for the aluminum plate and a net trained to monitor the 4th mode. A second excitation source was used to generate different levels of the 1st mode. The total variation of DCI is about 0.01 or about the RMS training error of the net. A fresh hologram pair is acquired for each sub-sampled pattern; hence other hologram-to-hologram elements of variation, in addition to the speckle effect, are learned.
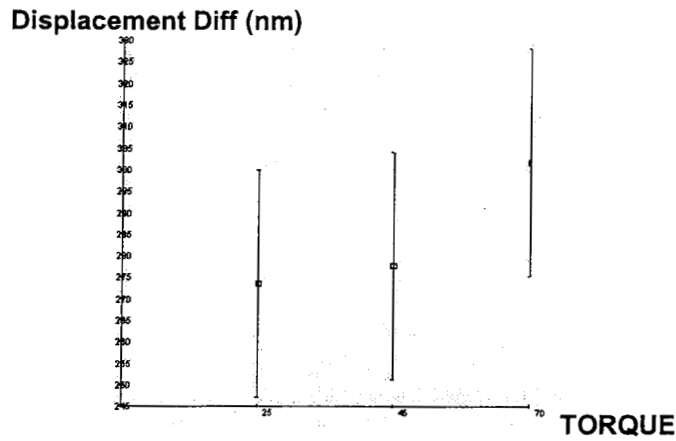
Displacement Diff (nm)

Fig. 8: Differential interferometer reading as a function of torque.
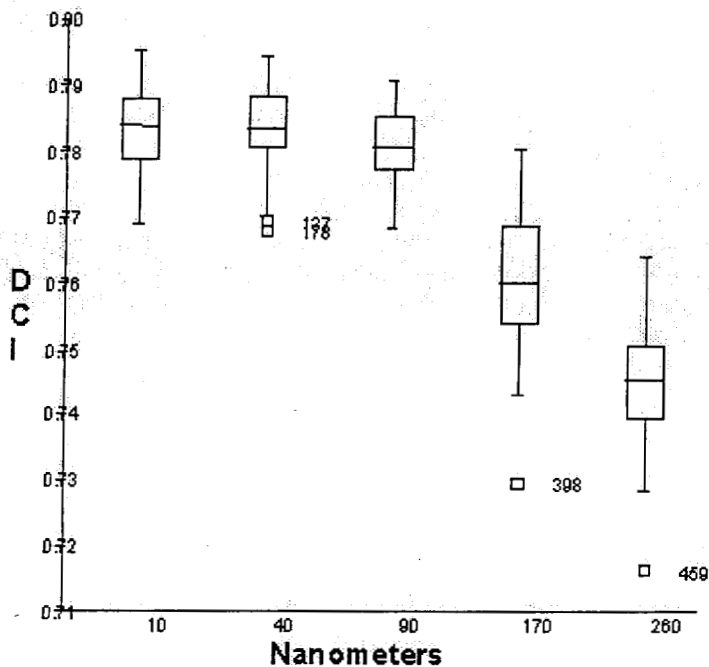

Fig. 9: Effect of first-mode noise on response of trained net to fourth mode. Horizontal axis displays peak-to-peak reading of heterodyne interferometer for first mode. Note that separations between horizontal points are not constant.

7. CONCLUDING REMARKS

The development of the method for NDE of structures based on neural-net processing of characteristic patterns is complete. A repeatable calibration procedure has been proposed that allows the net response to

first mode is the source of vibration noise. Figure 6 displays the neural-net performance for the various resolutions.

The same preparatory procedure was used for all the tests. The 8 screws were adjusted to 70 in lb. The torque of the second screw from the top on the left was then adjusted during a test. The vibration mode of interest was tuned to resonance while observing the characteristic pattern in real time. The heterodyne interferometer was then used to set a vibration amplitude. The NDE method has been used successfully over a large range of amplitudes, but the usual objective is to maintain high-contrast fringes in the recorded region. The so-called Bessel fringes as in Fig. 2 decrease in brightness and contrast as the vibration amplitude increases, hence smaller vibration amplitudes are usually selected. The 5th vibration mode was selected for the first training category and excited to a peak-to-peak vibration level of 0.32 μm or 320 nm as measured by the interferometer. A vibration level was estimated by viewing the interferometer output of several cycles of vibration graphed on a computer monitor. These cycles of course were observed to modulate varying levels of the first-mode The 5th mode was measured for the copper plate to have the largest variation in resonant frequency (about 6 Hz) as the torque was varied from 0 to 70 in lb. Training was accomplished at a torque setting of 25 in lb. The number of uncorrelated speckle patterns recorded varied from 11 for the 108-sample case to 692 for the 6912-sample case in accordance with the 10-percent rule. Note that the 10-percent rule was originally developed from modeled data, whereas experimental data contains other random effects as well. Nets have proven to be reasonably insensitive to amplitude fluctuations of the mode being monitored, indicating that they are responding to mode-shape variations. The first mode has a minimal effect as will be discussed later. Techniques for handling independent random effects in a training set are discussed in a reference.[4]

DCI

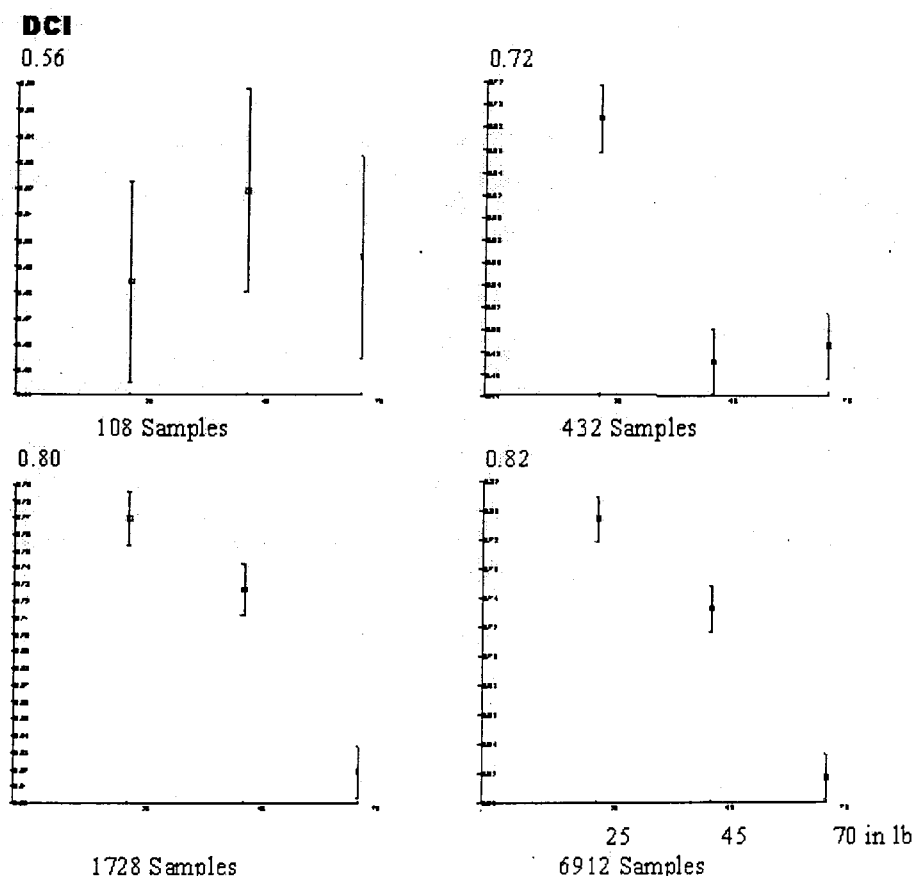| 0.56	0.72
108 Samples	432 Samples
0.80	0.82
1728 Samples	6912 Samples

25   45   70 in lb

Fig. 6: Neural-net performance variation with increasing sample size.

be correlated with the responses of other sensors used for vibration testing. The problem now is to discover how to use those sensors to best exploit the proven robustness of the optical NDE method discussed in this paper. The heterodyne interferometer was used as a displacement sensor to show the difficulty of handling the noise sources that the neural net handles easily. The performance of the neural network does improve with increasing resolution; hence increasing the resolution limit beyond the current 10,000 samples of the characteristic pattern is justifiable. There are other interesting R&D, as well as applications, questions to be answered. The use of multiple regions for NDE, each region having lower resolution, needs to be tested. Controlling sensitivity by varying the vibration-mode-mix requires additional study. The source of the torque-dependence of variance needs to be explained where the second training category consists of versions of the same mode. There is a conjecture that the general algorithm for assembling training data can be applied to other kinds of image data. That conjecture requires testing. The NDE method is sufficiently routine now that it easily can be adapted to applications such as health monitoring of spacecraft components during possibly destructive tests.

REFERENCES

1.   A. J. Decker, M. E. Melis and K. E. Weiland, "Inspection of Space Station Cold Plate Using Visual and Automated Holographic Techniques," *NASA/TM—1999-209388*, Aug. 1999.
2.   A. J. Decker, "Optimization of training sets for neural-net processing of characteristic patterns from vibrating solids," in *Optical Diagnostics for Fluids, Solids, and Combustion,* Carolyn.R. Mercer, Soyoung. S. Cha, Gongxin Shen, Editors, Proceedings of SPIE Vol. 4448, 209-217 (2001).
3.   A. J. Decker, "Neural-Net Processed Characteristic Patterns for Measurement of Structural Integrity of Pressure Cycled Components," *Proceedings of JANNAF, 12th Nondestructive Evaluation Subcommittee,* Cocoa Beach, Florida, 26-30 March 2001.
4.   A. J. Decker, "Neural-Net Processed Electronic Holography for Rotating Machines," *NASA/TM—2003-212218,* Feb. 2003.
5.   A. J. Decker, "Damage Detection Using Holography and Interferometry," in *Optical Metrology for Fluids, Combustion, and Solids,* Carolyn R. Mercer, Editor, Chapter 14, Kluwer Academic.
6.   "Dynamic Environmental Criteria." *NASA-HDBK-7005,* (2000).
7.   J. Lekki, G. Adamovsky, P. Flanagan and K. Weiland, "Evaluation of mechanical modal characteristics using optical techniques," *NASA TM 2002-211678 (2002).*
8.   A. J. Decker, E. B. Fite, O. Mehmed and S. A. Thorp, "Processing speckle patterns with model trained neural networks," in *Optical Technology in Fluid, Thermal, and Combustion Flow III,* Soyoung S. Cha, James D. Trolinger and Masaaki Kawahashi, Editors, Proceedings of SPIE Vol. 3172, 285-293 (1997).
9.   *RS/Series Release 5.3,* Domain Solutions Corporation, Cambridge (1997).